ABSTRACT: The afferent signals recorded with a multi-electrode cuff on the sciatic nerve were employed to investigate the possibility of extracting components ascending from the peroneal and tibial nerves. Two methods, an inverse regression model and principal component method, were studied. The parameters of inverse regression model, determined by data collected in semistatic conditions, were validated by data collected in dynamic conditions. The results showed that the regression model, which used only two channels of the sciatic recordings, was sufficient to separate the distal afferent components. The model, at the expense of requiring distal branch recordings for estimating model parameters, yielded better separation than the principal component method. In conclusion, peroneal and tibial afferent activity can be estimated from the sciatic nerve: the principal component method is suitable for applications focused on acquiring afferent information, whereas the inverse regression model is better for applications in which stimulations will be applied to the branches. The estimation technique provides a powerful tool for in vivo investigation of sensory information transmitted in a peripheral nerve and facilitates implementation of advanced functional neuromuscular stimulation systems.

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ESTIMATION OF PERONEAL AND TIBIAL AFFERENT ACTIVITY FROM A MULTICHANNEL CUFF PLACED ON THE SCIATIC NERVE

HANG-SHING CHENG, MS,1 MING-SHAUNG JU, PhD,1 and CHOU-CHING K. LIN, MD, PhD2

1 Department of Mechanical Engineering, National Cheng Kung University, Tainan, 701 Taiwan
2 Department of Neurology, Medical Center, National Cheng Kung University, Tainan, 701 Taiwan

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Functional neuromuscular stimulation (FNS) combined with artificial sensory feedback has a high potential for restoring motor functions of stroke patients.7,23 One technique is to employ afferent muscle spindle activity measured epineurally from a peripheral nerve as the feedback signal for the FNS system. This kind of closed-loop system that combines FNS control and neural prostheses has the advantage of total implantation. Recently, methods were proposed to achieve such closed-loop FNS control by extracting other sensory signals from cuff recordings, such as detection of heel contact while a patient with foot-drop problem is walking6 or detection of slip occurrence while a subject is gripping a weight.4,5 In both approaches, the nerve signals were recorded via the cuff electrodes on nerves and electrical stimuli were applied to the target muscle groups to achieve specific sensing and motor functions.

Other approaches focus on applying electrical stimulation directly to the nerve trunk via another cuff electrode. For example, the muscle spindle activity extracted from the tibial and peroneal nerves was employed as feedback signals to control ankle joint angle through the application of electrical stimulation on the tibial nerve.28 In another example, hypoglossal nerve afferent activity was used for closed-loop electrical stimulation of the hypoglossal nerve to treat upper airway obstruction.22,27 The advantage of imposing electrical stimuli directly on a nerve trunk is that a smaller current is required to evoke action potentials in nerve fibers. Since the intensity of muscle afferent signals is modulated by the movement of a joint,8,9,12,18 the simultaneous measurement of afferent signals from agonist and antagonist muscles could be used to trace the joint angle trajectory.1,10,15

In most previous investigations, cuff electrodes were implanted on the distal branches of a multifascicular nerve to measure the afferent signals from the target source and other cuffs were colocated on
these branches for more focused electrical stimulation. From a practical consideration, selective sensing or selective stimulation of a main nerve trunk by the use of multichannel cuff electrode is a feasible technique to separate the cuff recordings of a proximal nerve into the components from distal fascicles. For example, the tibial and peroneal nerves, which innervate the lateral gastrocnemius and the tibialis anterior, respectively, are the two major distal branches of the sciatic nerve. Electroneurographic (ENG) signal recorded from sciatic nerve should contain afferent signals from these two branches. In one study, a 33-electrode cuff (11 sets of tripolar electrodes) was employed to collect the ENG signals from the sciatic nerve of a dog while either the ankle was rotated or an extending force was applied to the gastrocnemius muscle. Natural sensory activity could be selectively recorded by using the multi-electrode cuff system, and consistency between the recorded ENG signals and the joint rotation was observed in some channels of the cuff recordings. The authors conjectured that the ENG detected on the sciatic nerve, with its two fascicles ascending from the tibial and peroneal nerves, could be separated into two independent components.

The main goal of this study was to test the plausibility of simultaneously estimating tibial and peroneal ENG from a single multichannel cuff electrode placed on the sciatic nerve. First, we built a semistatic model over the whole joint angle range. An empirical inverse linear regression model was obtained by relating the sciatic, tibial, and peroneal nerve signals when the ankle was rotated stepwise. Second, we validated the model in dynamic conditions. The signals detected from the sciatic nerve were decomposed into peroneal and tibial components when the ankle was stretched sinusoidally. The estimated component signals were compared with the corresponding signals detected directly from peroneal and tibial nerves. Finally, we compared the model with another decomposition technique, the principal component method, and probed the possibility of reducing the complexity of the regression model. In one subject, the separated signals were used to trace the ankle joint angle trajectory in the ramp-and-hold flexion–extension movements.

This study is part of a long-term project to implement autologous afferent sensing and electrical stimulation on nerves for ankle position control (Fig. 1). The results may also be used to monitor afferents from distal branches from a single cuff electrode implantation.

**MATERIALS AND METHODS**

The experimental procedure was approved by our institutional animal ethics committee. Acute experiments were performed using five adult male New Zealand white rabbits weighing 2.5–3.0 kg.

**Animal Preparation and Cuff Electrode Implantation.**

The animals were anesthetized with a constant infusion of ketamine (0.13–0.2 ml/min) intravenously before the experiment trials were commenced and with a lower rate of ketamine infusion (0.1–0.15 ml/min) during the experiments. An experienced investigator made an incision with an approximate length of 3 cm on the lateral side of the rabbit’s thigh obliquely down to below the popliteal fossa and exposed the sciatic nerve and its branches. The tibial and peroneal nerves were mobilized over a
sufficient length to permit the installation of the cuff electrodes on each of the three nerves.

A 4 × 2 (four-channel bipolar) spiral cuff electrode (Fig. 2) was implanted around the sciatic nerve and two 1 × 2 (one-channel bipolar) spiral cuff electrodes were each implanted around the tibial and peroneal nerves to record ENG signals extraneurally. The cuff electrodes were developed by the Man-Machine System Laboratory at our institution. These cuff electrodes had a three-layer structure, i.e., two polyimide sheets serving as insulating and shielding layers sandwiching a gold sheet with a predefined shape. The electrodes had a total thickness of 50 μm and were fabricated by micro-electromechanical system (MEMS) techniques. The exposed area of one square gold sensing electrode on the 4 × 2 multichannel cuff was 0.8 × 0.8 mm². The exposed rectangular gold sensing regions of the 1 × 2 one-channel bipolar cuff had a width of 1 mm and a length of 6 mm along the circumferential direction. The sensing areas of electrode pairs on both types of cuffs had a center-to-center distance of 8 mm along the longitudinal axis. All the cuffs had a length of 13 mm and a primary inner diameter of approximately 1.8 mm. The width and curvature of the spiral cuff were designed so that the electrodes would make good contact with the nerve, but the cuff imposed only small compression force on the nerve trunk. The first pair of bipolar electrodes was assigned to channel 1, and the following pairs sequentially to channels 2 to 4.

**Linear Regression Model for Separating the Multichannel Cuff Recordings.** The aggregate ENG signal recorded from the superficial region of a peripheral nerve can be considered a white signal with embedded sensory afferent activities. In general, the amplitude of ENG features correlates with the intensity of the afferent signal. In order to quantify the ENG signal, the root mean square (RMS) of the signal was used to derive features of the ENG signals. The cuff recordings at the sciatic nerve were assumed to be the summation of contributions from the tibial and peroneal fascicles, i.e.,

$$\hat{e}_s = a_1 e_1 + b_1 e_2 + c$$

where $\hat{e}_s$ was the estimated RMS of the sciatic ENG signal and $e_1$ and $e_2$ were the RMS of ENG signals recorded from the distal tibial and peroneal nerves, respectively. These two ENG signals were assumed to be proportional to the tibial and peroneal components inside the sciatic nerve trunk. To simplify the regression model, the three sets of parameters, namely, $a$, $b$, and $c$, were assumed as constants. The symbols $a$ and $b$ represented the time-invariant relationship between the fascicle signals and the aggregate cuff recording, and $c$ was a scalar-biased term. These parameters depended only on the location and orientation of electrode placement, and they were assumed to be constant during the acute experiment. To obtain the optimal parameters of the regression model, the ENG signals of sciatic, tibial, and peroneal nerves were measured simultaneously while the ankle joint was positioned systematically at various joint angles. The parameters were determined by minimizing the square error between the measured sciatic RMS ENG signal and the estimated one that was calculated by using eq. 1. In order to decompose the sciatic ENG signals and separate the tibial and peroneal components from the measured sciatic nerve signals, eq. 1 had to be inverted. Two regressive equations of sciatic nerve signals recorded at different orientations were used to obtain the inverse equations as shown in eqs. 2 and 3.

$$\hat{e}_t = \alpha_1 e_1 + \beta_1 e_2 + \gamma_1 = \frac{b_2}{a_1 b_2 - a_2 b_1} e_1 + \frac{-b_1}{a_1 b_2 - a_2 b_1} e_2$$

$$+ \frac{b_2 e_2 - b_2 e_1}{a_1 b_2 - a_2 b_1}$$

$$\hat{e}_p = \alpha_2 e_1 + \beta_2 e_2 + \gamma_2 = \frac{-a_2}{a_1 b_2 - a_2 b_1} e_1 + \frac{a_1}{a_1 b_2 - a_2 b_1} e_2$$

$$+ \frac{a_2 e_1 - a_2 e_2}{a_1 b_2 - a_2 b_1}$$

where $\hat{e}_t$ and $\hat{e}_p$ were the estimated tibial and peroneal RMS ENG signals by using the two sciatic RMS ENG signals, $e_1$ and $e_2$, recorded in different channels of the four-channel cuff. The parameters $\alpha, \beta, \gamma, \alpha', \beta', \gamma'$ of the inverse equations were all constants and determined by the parameters $a_1, b_1, c_1, a_2, b_2, c_2$ of the regressive equation (eq. 1) associated with the two sciatic ENG signals. The model was then validated by using the data obtained from sinusoidal stretches of ankle and was compared

![FIGURE 2. Cuff electrode arrangement.](image-url)
with another popular decomposition method, the principal component analysis.

Separating the Multi-ENG Signals by the Principal Component Method. For comparison, the two independent components that had the largest contribution were extracted from the four-channel sciatic ENG signals by using principal component analysis. The principal component analysis is analogous to a coordinate transformation, so that the recorded signals, when projected to the new coordinate system, became independent of each other.\textsuperscript{14,17} It was postulated that the transformed main components represented the components mainly from the tibial and peroneal fascicles, respectively. The correlation matrix, $R$, had the elements, $r_{ij}$, which represented the correlation coefficient of the RMS ENG signals between channel $i$ and channel $j$ of the sciatic cuff recordings. Firstly, the eigenvalues, $\lambda_i$, of the correlation matrix were calculated by

$$R_{xx} = \lambda_i x_i,$$  \hspace{1cm} (4)

where $x_i$ was the eigenvector associated with the eigenvalue, $\lambda_i$ and $i$ indexed from 1 to 4. The first principal component was a linear combination of the measured sciatic RMS ENG signals, with the coefficients which were the elements of the eigenvector, $x_i$, associated with the largest eigenvalue. In other words,

$$\hat{e}_i \ (\text{or} \ \hat{e}_j) = mx^T e_i,$$ \hspace{1cm} (5)

where $m$ was a scalar factor for equalizing the average of $x^T e_i$ and the average of the tibial (or peroneal) RMS ENG signals in the experiment. The first principal component was assumed to be one of the two fascicular signals based on the correlation between the estimated component and the measured RMS ENG signal of tibial or peroneal nerve. Similarly, the second principal component was assumed to be the signal ascending from the other nerve. The ENG signals of the sciatic nerves measured at different ankle positions, i.e., in the static condition, were used to find the eigenvectors and the scalar factors. Secondly, the ENG signals in sinusoidal stretch, i.e., in the dynamic condition, were fed into eq. 5 with the derived eigenvectors and scalar factors for comparison with the results estimated by using the regression model in the previous section.

Experimental Procedures and ENG Signal Processing. The ENG signal contains the afferent activities from muscle spindle, Golgi tendon organ, and other proprioceptors. In general, the tibial nerve had larger activity while the ankle was placed toward dorsiflexion whereas the amplitude of afferent signal from peroneal nerve increased when the ankle was moved toward plantarflexion. In this study, for identifying the parameters of the regression model, the ENG signals of the three nerves were collected at different ankle angles in so-called step increment trials. The ankle was held at the full plantarflexion position and the sciatic ENG, tibial ENG, and peroneal ENG signals recorded over a period of 10 s. The ankle was then rotated manually step by step in the dorsiflexion direction in 10-degree increments until the ankle could not be further rotated. After the recording and before the next increment, a 20-s rest period was utilized to ensure the stress relaxation of the soft tissue and to eliminate transient responses in the ENG signals.

During the trials, the rabbit was placed on the test platform and one ankle was fixed in a custom-made rotatable manipulator. The trunk posture was adjusted such that the angle of the knee was 90°. A data acquisition system simultaneously recorded the joint angle and the ENG signals from the cuff electrodes. The collected data were stored in a computer and subsequently analyzed off-line. As shown in Figure 3, the ENG signals collected from the multichannel cuff electrode and the two single-channel cuff electrodes were preamplified with a gain of 50,000 and filtered by using an analog high-pass filter with a cutoff frequency of 100 Hz (ERS100c; Biopac Systems Inc., www.biopac.com). The analog signals were then converted into digital signals via the dSPACE 1104 development system (dSPACE Inc., www.dspaceinc.com) with a sampling rate of 10 kHz/channel. A second-order Butterworth high-pass filter with a 1-kHz cutoff frequency was used to reduce electromyography (EMG) artifacts.\textsuperscript{24,26} Figure 4 presented the power spectra of high-pass filtered peroneal nerve ENG signals at various ankle positions. It was clear that the power of the peroneal ENG signal increased with increasing ankle angle, though the spectrum of the ENG covered all the frequencies above the cutoff frequency. Although the contribution from the relaxed muscle (i.e., the EMG) was low, EMG might contaminate the ENG signal significantly during muscle contraction. Therefore, 1-kHz high-pass filtering was necessary if a clean ENG signal was to be obtained while electrical stimulation was applied simultaneously on the nerve or nearby muscles.\textsuperscript{26} In this study, RMS of the ENG signals was calculated over a moving time-window of 10 ms in order to derive the ENG features. Furthermore, in order to quantify the prediction
capability of the regression model, two indices were employed in this study, namely, RMS error and the $R^2$ value. All calculations were performed using Matlab software (The MathWorks Inc., Natick, Massachusetts).

To demonstrate the applicability of the linear regression model obtained in step increment trials, i.e., static conditions, to simple dynamic conditions, several trials of manual sinusoidal stretches were performed on the rabbit’s ankle. First, the ankle was stretched within a limited range from 70° to 150° and continuously repeated for seven cycles. As shown in Figure 1, the angle, $\theta$, was measured between the foot and the lower leg of the rabbit and an increasing angle corresponded to plantarflexion. The frequency of sinusoidal stretch was about 0.5 Hz. The sciatic multichannel ENG signals were collected and fed into the regression model to estimate the tibial and peroneal ENG components, and then compared with the two measured ENG signals. Second, the stretch frequency was changed from 0.5 Hz to 1 Hz and 1.5 Hz and the movements were repeated seven more times. Finally, three stretches with a smaller amplitude of 15° and a fixed frequency of 1.5 Hz were performed at different positions. The mean positions of these three stretches were 80°, 100°, and 120°, respectively.

Finally, all the measured sciatic ENG signals in the sinusoidal trials were used to estimate the tibial and peroneal components by using both the regression model and the principal component method, whose parameters were obtained from step increment trials. Statistical comparisons between these two methods were performed with two-sample $t$-test ($\alpha = 0.05$).

Trials of ramp-and-hold flexion–extension movements were performed in one subject (rabbit 5) in a similar way to the sinusoidal trials.

**RESULTS**

**Step Increment Experiment and Parameter Estimation of Linear Regression Models.** A total of six channels of ENG from the sciatic, tibial, and peroneal nerves were collected in step increment trials, and the RMS values of these ENG signals were calculated. As a typical example, the averages over the 10 s measurement of the six RMS ENG signals of rabbit 1 at different ankle positions are shown in Figure 5. The peroneal RMS ENG signal increased with the ankle in a plantarflexion direction, whereas the tibial RMS
ENG signal increased in dorsiflexion direction. Four RMS ENG signals of the sciatic nerve had a similar trend of higher amplitudes in both directions toward extreme joint angles, but the slopes and curvatures were different. Based on this observation, a linear regression model was proposed to separate the multichannel cuff recordings of the sciatic nerve. Channel 3 of sciatic RMS ENG signal had a higher consistency with the tibial signal, whereas channel 4 had a higher consistency with the peroneal signal.

The regression models of the four sciatic cuff recordings were obtained by minimizing the squared estimated errors. Fourteen RMS values of tibial nerve signal and 14 values of peroneal nerve signal measured in the step increment trial were used to estimate the sciatic RMS ENG signals at different joint positions. Results of the regression models of five rabbits are listed on Table 1, including the parameters and the RMS errors and $R^2$ values between the estimated signals ($\hat{e}$) and the measured signals ($e$). The small RMS error and large correlation $R^2$ revealed that the linear regression model was a satisfactory method for separating ENG signals.

### Table 1. Parameters and estimation indices of sciatic nerve signals.

<table>
<thead>
<tr>
<th>Rabbit no.</th>
<th>Sciatric nerve</th>
<th>$\hat{\delta}_i = a \delta_i + b \phi_i + c$</th>
<th>RMS error (µV)</th>
<th>$R^2$ value</th>
<th>Selected channel (*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ch1</td>
<td>1.330 0.143 -0.56</td>
<td>0.00971</td>
<td>0.9876</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch2</td>
<td>1.514 0.307 -0.64</td>
<td>0.01223</td>
<td>0.9686</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch3</td>
<td>2.785 0.564 -2.057</td>
<td>0.01315</td>
<td>0.9909</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch4</td>
<td>1.537 0.904 -1.011</td>
<td>0.01277</td>
<td>0.9629</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>ch1</td>
<td>0.325 0.073 1.142</td>
<td>0.01547</td>
<td>0.9109</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch2</td>
<td>0.201 -0.953 4.619</td>
<td>0.07727</td>
<td>0.7999</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch3</td>
<td>1.015 -0.786 1.564</td>
<td>0.03029</td>
<td>0.9854</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch4</td>
<td>1.404 0.293 0.522</td>
<td>0.01111</td>
<td>0.9981</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>ch1</td>
<td>-0.354 1.236 0.459</td>
<td>0.02001</td>
<td>0.9212</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch2</td>
<td>0.774 2.704 2.081</td>
<td>0.03143</td>
<td>0.9557</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch3</td>
<td>1.638 2.212 -2.268</td>
<td>0.01944</td>
<td>0.9895</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch4</td>
<td>1.494 0.531 -0.194</td>
<td>0.03299</td>
<td>0.9524</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>ch1</td>
<td>-0.064 0.228 3.051</td>
<td>0.04471</td>
<td>0.7347</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch2</td>
<td>0.275 0.141 0.771</td>
<td>0.01119</td>
<td>0.9448</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch3</td>
<td>0.631 0.162 0.599</td>
<td>0.00888</td>
<td>0.9923</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch4</td>
<td>0.796 0.111 0.540</td>
<td>0.00699</td>
<td>0.9972</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>ch1</td>
<td>0.187 0.116 2.038</td>
<td>0.01142</td>
<td>0.8389</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch2</td>
<td>-0.231 0.005 5.092</td>
<td>0.02701</td>
<td>0.7457</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch3</td>
<td>1.912 0.55 -0.607</td>
<td>0.01575</td>
<td>0.9964</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ch4</td>
<td>1.162 1.051 -1.063</td>
<td>0.01246</td>
<td>0.997</td>
<td></td>
</tr>
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</table>
measured and estimated results in step increment trials. The dark and light gray regions covered the ranges of one standard deviation of tibial and peroneal RMS ENG signals from the mean values. The RMS errors between the fitted and experimental data were 0.00767 μV and 0.02265 μV for the tibial and peroneal components, respectively. The errors were significantly less than the standard deviation in the RMS ENG. Complete results of the component estimation are listed in Table 2. The results revealed that the tibial and peroneal components could be separated by means of the inverse linear regression model, and only two out of four sciatic RMS ENG signals were utilized.

To demonstrate the extensibility of the inverse regression models, several manual sinusoidal stretches were performed on the rabbit’s ankle. The cuff electrode system remained implanted, and all the conditions for ENG measurement were identical to those in step increment trials. The results of one example stretch in rabbit 1 are shown in Figure 7, including (a) the angular trajectory of ankle, (b) the tibial ENG signal, (c) the peroneal ENG signal, and (d–g) the four channels of sciatic ENG signals. The ankle was stretched within the amplitude range of 40° and with a stretch frequency of 0.5 Hz. The ENG of the tibial and peroneal nerves were out of phase by approximately 180° during the sinusoidal stretch. In this rabbit, channels 3 and 4 were chosen to estimate the fascicle components. The ankle trajectory and the RMS traces of sciatic (two channels), tibial, and peroneal ENG signals are shown as solid lines in the left panels of Figure 8. The dotted lines in the two lower panels are the estimated tibial and peroneal RMS ENG signals by using Table 2.

### Table 2. Inverse regressive equations to estimate tibial and peroneal components and their performance indices.

<table>
<thead>
<tr>
<th>Rabbit no.</th>
<th>Nerve</th>
<th>Linear regressive equation</th>
<th>RMS error (μV)</th>
<th>$R^2$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Tibial</td>
<td>$d_t = 0.5478e_{t_a} - 0.3419e_{t_d} + 0.7815$</td>
<td>0.00767</td>
<td>0.9898</td>
</tr>
<tr>
<td></td>
<td>Peroneal</td>
<td>$d_p = -0.9317e_{t_a} + 1.688e_{t_d} - 0.2103$</td>
<td>0.02265</td>
<td>0.9348</td>
</tr>
<tr>
<td>2</td>
<td>Tibial</td>
<td>$d_t = 0.2089e_{t_a} + 0.5311e_{t_d} - 0.0342$</td>
<td>0.04815</td>
<td>0.9983</td>
</tr>
<tr>
<td></td>
<td>Peroneal</td>
<td>$d_p = -1.0031e_{t_a} - 0.7247e_{t_d} + 1.9469$</td>
<td>0.03450</td>
<td>0.9408</td>
</tr>
<tr>
<td>3</td>
<td>Tibial</td>
<td>$d_t = -0.1463e_{t_a} + 0.7451e_{t_d} - 0.1597$</td>
<td>0.02628</td>
<td>0.9327</td>
</tr>
<tr>
<td></td>
<td>Peroneal</td>
<td>$d_p = 0.4117e_{t_a} - 0.2133e_{t_d} + 0.8153$</td>
<td>0.01642</td>
<td>0.8911</td>
</tr>
<tr>
<td>4</td>
<td>Tibial</td>
<td>$d_t = -1.3612e_{t_a} + 1.7258e_{t_d} + 0.1177$</td>
<td>0.01756</td>
<td>0.4659</td>
</tr>
<tr>
<td></td>
<td>Peroneal</td>
<td>$d_p = 9.7575e_{t_a} - 3.3706e_{t_d} + 5.7006$</td>
<td>0.10730</td>
<td>0.9850</td>
</tr>
<tr>
<td>5</td>
<td>Tibial</td>
<td>$d_t = 0.7667e_{t_a} - 0.4000e_{t_d} + 0.0397$</td>
<td>0.01447</td>
<td>0.9980</td>
</tr>
<tr>
<td></td>
<td>Peroneal</td>
<td>$d_p = -0.8475e_{t_a} + 1.3944e_{t_d} + 0.9671$</td>
<td>0.01001</td>
<td>0.9970</td>
</tr>
</tbody>
</table>

![Figure 6](image.png)

**Figure 6.** Channels 3 and 4 of the sciatic RMS ENG signals of rabbit 1 in step trials were used to estimate the tibial and peroneal RMS ENG signals by using the regression model. The dark and light gray regions represent the ranges within one standard deviation of averaged measured tibial and peroneal RMS ENG signals, respectively.

![Figure 7](image.png)

**Figure 7.** Angular trajectory of the ankle and the results of ENG measurement during a sinusoidal stretch trial with a range from 70° to 150° and a frequency of 0.5 Hz.
the sciatic RMS ENG signals and the inverse regression model. The results showed that the inverse regression model had an excellent capability of estimating the tibial component but had a notable bias in the peroneal component. This outcome corresponded with the observation in Figure 7, in which the four measured sciatic signals had a higher consistency with the tibial signal. In other words, the afferent signal from the tibial fascicle dominated the sciatic cuff recordings in rabbit 1. The results of rabbit 3 subjected to a manually sinusoidal stretch with a range of 80° and a frequency of 1.5 Hz are shown in the right panels of Figure 8. Channels 2 and 4 were chosen to estimate the fascicle components. Since channel 2 had a high consistency with the peroneal signal, the estimation error in the peroneal branch was less than that in the tibial branch. Generally, as shown in these two examples, the regression models obtained in the step increment trials performed satisfactorily in the sinusoidal stretch trials.

Comparison between Linear Regression Model and Principal Component Method. The performances of the inverse linear regression model and the principal component method in the sinusoidal stretch trials were compared. The RMS errors and $R^2$ values between the measured and estimated RMS ENG signals in all five rabbits were calculated, and they included six trials of sinusoidal stretches, and each trial had five repeated cycles. Figure 9 summarizes the averages of the RMS errors in tibial estimates (upper panel) and peroneal estimates (lower panel). In each panel, the left three groups of data were the results of stretches between 70° and 150° and with frequencies of 0.5 Hz, 1 Hz, and 1.5 Hz, respectively. The three groups of data on the right were the results of the stretches with different mean positions (80°, 100°, and 120°). For the tibial ENG signal, the inverse regression model had less RMS errors in all cases of stretches than those of the principal component method, although only four in six cases reached statistical significance. The accuracy of estimation by using the inverse regression model was better than using the principal component method for all passive sinusoidal stretches. For estimating the peroneal ENG signal, the RMS errors associated with the inverse regression model were significantly less than those with the principal component method in all six cases. The statistical analyses results of the $R^2$ values in tibial estimation (upper panel) and peroneal estimation (lower panel) are shown in Figure 10. Although, in most cases, there was no significant difference between the $R^2$ values of the regression model and the principal component method, the

FIGURE 8. Left panels: results of sinusoidal stretch of rabbit 1, including the ankle trajectory, measured RMS ENG signals (solid line) in channels 3 and 4 of sciatic, tibial, and peroneal cuffs, and estimated signals (dotted line). Right panels: results of rabbit 3.
group mean values of inverse regression model were larger than those of the principal component method in all cases. Both methods yielded smaller $R^2$ values and larger variances for estimating the peroneal ENG signal. In short, even though only two measured sciatic RMS ENG signals were used, whereas all four channels were used in the principal component method, better estimation of the peroneal and tibial components was achieved by using the inverse linear regression model.

Ankle Joint Angle Tracing by a Single Multichannel Cuff on the Sciatic Nerve. The angular trajectory of ankle subjected to a ramp-and-hold rotation and two channels of measured sciatic cuff recordings of rabbit 5 are shown in Figure 11. It can be seen that the inverse regression model performed well in estimating both peroneal and tibial components in these trials.

It was impossible to estimate the joint angles using only the raw sciatic ENG signals, because the relationship between the sciatic RMS ENG signal and the joint angle was not one-to-one. However, through signal decomposition (with either inverse regression model or principal component method), the afferent signals from agonist and antagonist could be separated and the trajectory of rotation could be roughly traced, as explained below. At 2 s, the tibial ENG suddenly declined and the peroneal ENG gradually increased. Based on this observation, rotation of ankle toward plantarflexion was judged to have occurred. Furthermore, though the change in tibial ENG was nonlinear at the ramp increase of joint angle, the increment of peroneal ENG was linearly correlated with the joint rotation. The angle trajectory could be roughly traced by using the peroneal ENG signal. Conversely, at 8 s, when dorsiflexion was performed, the roles of peroneal and tibial ENG signals were switched.

**DISCUSSION**

In a multifascicular nerve, the afferent signals measured at the main trunk contain components from the...
distal branches. In this work, a new method which employed only two channels of ENG signals detected from sciatic nerve was utilized to separate the ENG signals ascending from tibial and peroneal fascicles. The parameters, $a_{i1}$ and $a_{i2}$, were the important factors for determining whether the measured sciatic nerve signal was dominated by the tibial or peroneal component. For example, in rabbit 1, all the four channels had larger parameters associated with the tibial term. This is quite reasonable because, as shown in Figure 5, all the measured sciatic RMS ENG signals had larger amplitudes at dorsiflexion than those at plantarflexion. Therefore, a better performance of the tibial RMS ENG estimation in this rabbit was obtained. Since the tibial component was the dominant part of the measured sciatic RMS ENG signals, gaining a better estimation in tibial RMS ENG signal (Fig. 5) was justifiable. In all sinusoidal stretches of the ankle of rabbit 1, tibial estimation was also better than peroneal estimation either by using the regression model or principal component method. In fact, because the diameter of the tibial nerve was usually larger than that of the peroneal nerve, the component from the tibial branch usually dominated most channels of the sciatic cuff recordings. Further, in most cases the estimations of tibial ENG signal had better RMS error and $R^2$ value than those of peroneal signal.

Several investigators have used the multichannel cuff electrode to measure the nerve signals and shown the selectivity of ENG measurement by simulation models. The results in our study showed that both the inverse regression model and the principal component method had a satisfactory capability in estimating the tibial and peroneal RMS ENG signals. Even in the sinusoidal trials, the estimated errors were smaller than the variance of RMS ENG signals (Fig. 7). Therefore, the proposed decomposition techniques were suitable for estimating the component features in multichannel nerve signals.

The main idea of the principal component method is to find the independent components in which the first principal component (or vector) is along the direction of maximum variance from origin, and the following components are orthogonal to the determined ones. When the ankle of a rabbit was subjected to passive stretches, group Ia muscle afferent signals from muscle spindles dominated the ENG signal in the nerve because the afferents were dependent on the muscle length and on the rate of muscle-length change. Since the conditions were different, using the principal components derived from the step increment trials to estimate the signals in sinusoidal trials might yield inferior estimation performance. However, in the regression model, the parameters were assumed to be time-invariant and were considered related only to electrode placement. Therefore, no matter what afferent signals were transmitted in the nerve, satisfactory estimation could be obtained. One more advantage of the inverse regression model was the simplicity of equations and a smaller load of calculations, which made real-time implementation plausible. The main limitation of the regression model was that the parameter set of the model had first to be found. Three cuffs, including sciatic, peroneal, and tibial cuffs, had to be implanted on the nerves simultaneously to collect ENG signals for parameter estimation. The principal component method required only sciatic recordings. In short, the regression model had better performance at the expense of demanding more inputs. The choice of which method to use in the future may depend on the application. For applications focused solely on acquiring afferent information, the principal component method is desirable, because only the sciatic cuff has to be implanted. For applications in which stimulations will be applied to the branches, the inverse regression model is better, because the cuffs are already in place and the model has better performance.

As shown in Figure 5, the mapping from the sciatic RMS ENG signal to the joint angle was not one-to-one.
Joint-angle tracing. In the past, the simultaneous feature evaluation also aggravated the difficulty of agonist and antagonist. Building up such a mathematical relationship between the ent velocities and different ranges, are needed to establish more rigorously the relationship between the joint angle trajectory and the afferent signals from the peroneal recordings faithfully and raised the possibility of angle tracing by a single cuff. Further experiments, i.e., passive ramp-and-hold stretches with different velocities and different ranges, are needed to establish more rigorously the relationship between the joint angle trajectory and the afferent signals from the agonist and antagonist. Building up such a mathematical model, which includes angular velocity terms to describe the transient response and decay of afferent signals (caused by relaxation of intrafusal muscle fibers of the spindle), is the goal of future studies.

A signal decomposition technique is one of the core components in feedback control for functional electrical stimulation. Adding the afferent information and the associated feedback control makes the electrical stimulation more specific and precise. In addition to the original purpose, this technique, capable of continuous real-time monitoring of afferent signals from distal branches, can be a powerful tool for clinical and basic research. For example, the relationship between afferent activities and the benefits of measures to reduce spasticity can be investigated, as can the relationship between agonist and antagonist afferent activities in various patterns of movement.

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